SPATIAL STATISTICS OF EPIDEMIC DATA: THE CASE OF DIABETES IN TARABA STATE

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Abstract

In this study, we applied Spatial Binary Logistic Regression Model (SBLRM) to predict the spread of diabetes epidemic infection, identify territories of high risk and determine important demographic and environmental factors that increase the risk of diabetes infection in Taraba State Nigeria. The monthly recorded cases of diabetes between January 2011 and December 2020 in the record department of Federal Medical Centre (FMC) Jalingo was used to measure the extent to which the odds in favour of being diabetic are raised when the levels of each explanatory variable is raised from the reference level (low) to the highest level (high), Thus, it shows that risk factors is the strongest determinant of being diabetic having $EXP(\beta)$ of 70.981 and the least is Sex which account for $EXP(\beta)$ of 09.504. Also the covariate (sex, marital status and height) are not statistically significant because they $EXP(\beta)$ represent the odd ratio which measure the extent to which odds in favour of positive response are raised. While the p-values (age, risk factors, weight, blood pressure and blood sugar level) are statistically significant because their p-values are less than 0.05 (<0.05). The SBLRM could be applied to effectively predict the spread of diabetes disease in Taraba State Nigeria and provide support for the development of interventions for diabetes disease control and prevention.

Keywords: Diabetes, Explanatory Variables, Risk factors, p-values

Introduction

Background of the Study

Diabetes mellitus is a chronic non-communicable disease associated with long term complications to the brain, kidney, and the heart. There is destruction and loss of the s-cells of the pancreas causing insulin deficiency; it may also result from abnormalities arising from resistance to insulin. Symptoms of hyperglycaemia include polydipsia, polyphagia polyuria, blurred vision, weight loss, generalized pruritus, neuropathy, retinopathy, etc. Life threatening consequences of uncontrolled diabetes include diabetes-ketoacidosis, lactic acidosis and hyper-osmolar non-ketotic state (Diabetes Care, 2006). Diabetes is preceded by impaired fasting glucose (IFG) resulting in a pre-diabetic state which can exist undetected for many years, (Nathan et al., 2007) causing irreversible damage to vital organs. Pre-diabetes is a practical term referring to Impaired Fasting Glucose (IFG), impaired glucose tolerance (Ronald & Zubin, 2013) or a glycosylated haemoglobin (A1c) of 6.0 to 6.4%, each of which places individuals at high risk of developing diabetes and it complications. The World Health Organization criteria for diagnosing pre-diabetes are fasting plasma glucose level of between 6.1 and 6.9 mmol/l. A fasting plasma glucose level 7.0 mmol/l or more meets the criteria for the diagnosis of diabetes. Fasting value for venous and capillary plasma glucose are identical (Yin *et. al*., 2015)

There is an increasing prevalence of diabetes and pre-diabetes worldwide (Zhu *et. al*., 2012). Over 5 million people suffer from the disease in Africa and the number is expected to skyrocket to 15 million by 2025 (Zhu *et. al.*, 2012). In Nigeria the prevalence varies from 0.65% in rural Mangu village to 11.0% in urban Lagos (Akinkugbe, 1997). With the incidence of diabetes in Africa, diabetic complications are also expected to rise proportionately (Wild et al., 2004; Zimmet, 2003).

This will undoubtedly pose serious health and economic problems. The disease affects many people under the age of 64 years in Africa as compared to the developed world where it affects many people over the age of 64 years (Wild et al., 2004). In Nigeria the National prevalence of diabetes was 2.2% (Akinkugbe, 1997). In South Eastern Nigeria the overall prevalence of diabetes was 10.51% (Chris et al.,2012), whereas in South Western Nigeria the prevalence of diabetes ranges from 4.76% in Ile-Ife, Osun State to 11.0% in Lagos (Akinkugbe, 1997; International Diabetes Federation, 2006). Also 0.8% of diabetes mellitus, and 2.2% of Impaired Glucose Intolerance in Ibadan (Olatunbosun et al., 1998). This was comparable to WHO reported a prevalence of 2.8% in Ibadan (Owoaje et al., 1997), 1.7% in Ilorin (Martinez and Rojas., 2017; Ohwovoriole et al., 1988), and 6.8% in Port Harcourt, Nigeria (Nyenwe et al., 2003). In 2004, a survey in Jos (Nyenwe et al., 2003) reported a prevalence of 10.3%. Nyewe et al. (2003) reported a prevalence of 2.2% in Port Harcourt in 2003. A prevalence of 4.7% was reported by Lucia and Oliveira *et. al*.. (2012) which was higher than the national prevalence of 2.2% reported in the International Diabetes Federation in 2007. A review of studies on the prevalence of diabetes in adults in Africa by Unwin, Sobugwi, and Alberti (2001) and Azevedo and Alla (2008) demonstrated a rising prevalence across the continent.

Spatial epidemiology is the study of the spatial/geographical distribution of the incidence of disease and its relationship to potential risk factors. The origins of spatial epidemiology are dated back to 1855 with the seminal work of Snow on cholera transmission. He mapped the cholera cases together with the locations of water

source in London, and showed that contaminated water was the major cause of the disease. Spatial analysis in the nineteenth and twentieth century was mostly employed by plotting the observed disease cases or rates (Oguntoke, 2014).

Recent methods make use of computer based cartographic methods, satellite derived data and modern statistical methods and allow an integrated approach to address both tasks; inference on the geographical distribution of a disease and its prediction at new locations.

Spatial analysis could be defined as a quantitative data analysis which focuses on the role of space and relies explicitly on spatial variables in order to explain or predict the phenomenon under investigation

Statement of the Problem

Diabetes is a major cause of morbidity and mortality both in developing and developed countries. The incidence is rising rapidly with sub-Saharan Africa experiencing the largest percentage increase between 2013 and 2015. Nigeria has the largest number of people with the disease, yet information on the diabetes mellitus for policy and programming is fragmentary. Therefore, the purpose of this study is to systematically identify population-based studies on diabetes in Taraba State, Nigeria and to determine the prevalence, examine the sex urban/rural difference in these rates and temporal trends in the prevalence and also to use spatial statistics to show the distribution of these rates.

Aim and Objectives of the Study

The aim of this research work is to use spatial statistical methodologies to study the spatial patterns of diabetes with the following objectives to:

(i) Explore the spatial and demographic patterns of diabetes disease in Taraba State by local government areas

(ii) Identify territories of high risk and model some important demographic and environmental variables that increase the risk of infection in Taraba state

And analyse the significant difference between the means of such variables.

Significance of the Study

Findings of this research would be important to Health practitioners, Epidemiologists etc. and also add to the body of literature on spatial epidemiology studies.

Scope of the Study

This research is circumscribed to the application of spatial statistics on diabetes epidemiology data in Taraba State, Nigeria.

Source of Data

The data for this study is obtained from the records department of the Federal Medical Centre, Jalingo, Taraba State. Nigeria.

Research Methodology

Spatial Binary Logistic Regression modelling

Let Y_i be a binary response variable and N_i be the number of screened diabetic patients at location S_i (i.e. cluster centroid) respectively. Y_i is typically assumed to arise from a Binomial distribution, $Y_i \sim Bin(N_i, p_i)$ where pi indicates the probability of being diabetic at S_i. Binomial model assumes two sources of probabilities: θ_i (success probabilities) and the remaining $(1-\theta_i)$ is the probability of failure defined by a Binomial distribution, see equation

$$Y_i|p_i,\theta_i \sim \begin{cases} 1 & with\ prob\ \theta_i \\ 0 & with\ prob\ (1-\theta_i) \end{cases}$$

3.1

The relation between p_i and the vector of k associated predictors $X_i = (X_{i1},..., X_{ik})^T$ observed at location S_i is modelled via the equation

$$\text{logit}(p_i) = X_i\beta + \phi_i,$$

where $\beta_i = (\beta_1,..., \beta_k)$ is the regression coefficient vector, ϕ_i and is the random effect. Spatial dependence is introduced by assuming that the random effects $\phi_i = (\phi_1,..., \phi_n)$ is distributed according to a MVN distribution with mean 0 and covariance matrix $\sum$ where each element σ_{ij} is defined by an exponential parametric function of the distance between d_{ij} two locations S_j and S_i, i.e. $\sigma_{ij} = \sigma^2{}_\phi \exp(-\rho d_{ij})$.

Specification of the Model

In binary logistic regression applications, the response variable Y_i of interest has only two possible qualitative outcomes, and therefore can be represented by a binary indicator variable taking values 1 (if a patient is diabetic) and 0 (if a patient is not diabetic). A binary response variable, taking on the values 0 and 1, is said to involve binary responses or dichotomous responses.

The odd ratio is given by $\left[\frac{\theta_i}{1-\theta_i}\right]$

For a binomial response variable, the logistic (logit) is the natural logarithm of the odds ratio:

$$Y = probability(diabetic) = \ell n\left[\frac{\theta_i}{1-\theta_i}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_i x_i$$

β_0 = intercept

β_1 = Sex

β_2 = Age

β_3 = Marital Status(MS)

β_4 = Risk Factor(RF)

β_5 = Height(HT)

β_6 = Weight(WT)

β_7 = Blood Pressure(BP),

β_8 = Blood Sugar Level(BSL)

The equation intercept (constant) β_0 and variable coefficients β_i are estimated using maximum likelihood techniques. Once these are known, the model can be applied to estimate future states based on an alternative data set considering the same variables.

Wald Statistic and Likelihood Ratio Test

The Wald statistic and likelihood ratio test are used to assess the significance of the logistic regression coefficients.

$$Z = \hat{\beta}^2 \frac{1}{\left[S.E\left(\hat{\beta}\right)\right]^2}$$

Where $\hat{\beta}$ represents the estimated coefficient β and $S.E\left(\hat{\beta}\right)$ is its standard error. Under the null hypothesis of zero slope and based on asymptotic theory, this quantity follows a chi-square distribution with one degree of freedom. If the estimated value of the slope is small and its estimated variability is large, then we cannot conclude that the slope is significantly different from zero and vice versa (Afifi, Clark & May, 2004).

The likelihood ratio test for overall significance of the beta's coefficients for the independent variables in the model is used (Hosmer & Lemeshow, 2000). The test based on the statistic" G" under the null hypothesis that the beta's coefficients for the covariates in the model are equal to zero. G statistic takes the form:

$$G = -2\ell n\left[\frac{likelihood\ without\ the\ variable}{likelihood\ with\ the\ variable}\right]$$

The distribution of "G" is a chi-square with q degree-of-freedom, where q is the number of covariates in the logistic regression equation. (Jennings, 1986) examined the performance of the Wald test and found that, the test often failed to reject the null hypothesis when the coefficient was significant. They recommended that the likelihood ratio test to be used.

The likelihood statistic L is used to assess the fitness of the model. The sampling distribution of the – 2 log L, has a chi-square distribution with q degrees of freedom under the null hypothesis that, all regression coefficients of the model are zero. A significant $p-value$ provides evidence that, at least one of the regression coefficients for an explanatory variable is non-zero.

The odds ratio

The odds ratio is a measure of association for 2×2 contingency table (Agresti, 2007). In 2×2 tables the probability of "success" is π_1 in row 1 and π_2 in row 2. Within row 1, the odds of success are defined to be:

$$odds_1 = \frac{\theta_1}{1-\theta_1} \text{ and } odds_2 = \frac{\theta_2}{1-\theta_2}$$

(Agresti, 2007) defined the odds ratio in two groups of subjects as "the ratio of odds". Thus;

$$\theta = \frac{odds_1}{odds_2} = \frac{\theta_1/1-\theta_1}{\theta_2/1-\theta_2}$$

For the binary regression model, the odd ratio is the exponent $\left(e^{\beta_i}\right)$ i.e. the ratio of odds for a one-unit change in (Hosmer & Lemeshow, 2000). The change in Log odds, and the corresponding change in the odds ratio, for a c units is estimated $\exp\left[c\beta_i\right]$. When the two groups of odds are identical then the odds ratio is equal to one.

Analysis and Discussion of Results

Spatial Binary Logistic Regression modelling

Table 4.3: Variables in the Equation

	B	*S.E*	*Wald*	*Df*	*Sig*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Age	0.054	0.062	0.754	1	0.0385	65.055	0.935	1.192
Sex	14.866	9.022	0.000	1	0.0983	09.504	0.000	-
MS	-14.593	82.09	0.000	1	0.0996	10.000	0.000	-
RF	0.019	0.346	0.003	1	0.0355	70.981	0.498	1.932
HT	-4.214	6.579	0.410	1	0.0522	12.015	0.000	58.60
WT	0.033	0.065	0.252	1	0.0431	60.968	0.852	1.099
BP	0.093	0.135	0.474	1	0.0421	40.911	0.699	1.188
BSL	0.002	0.031	0.003	1	0.0395	68.998	0.940	1.060
Constant	28.106	58.06	0.000	1	0.993	16077.8		

From table 4.3 above, it could be noted that, the covariates (age, risk factor, weight, blood pressure and blood sugar level) are statistically significant, because they have a p-value of less than 0.05. Subsequently, the covariates (sex, marital status and height) are not statistically significant. The Exp (B) representing odds ratio, measures the extent to which the odds in favour of a positive response are raised when the level of the associated explanatory variable is raised from the reference level to the level specified in the table of results. This study measures the extent to which the odds in favour of being diabetic are raised when the levels of each explanatory variable is raised from the reference level (low) to the highest level (high). Thus, it shows that Risk Factor (RF) is the strongest determinant of being diabetic, having $Exp(\beta)$ of 70.981. Blood Sugar Level (BSL) is the second strongest determinant since the $Exp(\beta)$ accounts for 68.998. The third strongest determinant is Age since the $Exp(\beta)$ accounts for 65.055. Furthermore, Weight is the fourth strongest determinant having an $Exp(\beta)$ of 60.968. Blood Pressure (BP) accounts for $Exp(\beta)$ of 40.911. Height (HT) accounts for $Exp(\beta)$ of 12.015. Marital Status (MS) accounts for $Exp(\beta)$ of 10.000 and Sex accounts for $Exp(\beta)$ of 09.504. The explanatory variables (age, sex, risk factor, weight, blood pressure and blood sugar level) all have a positive influence on the response variable. Therefore, the logistic regression model for the variables that affect a patient being diabetic is as follows:

$$Y = probability(diabetic) = \ell n\left[\frac{\theta_i}{1-\theta_i}\right]$$

$$= 28.106 + 0.054X_1 + 14.866X_2 - 14.593X_3 + 0.019X_4 - 4.214X_5 + 0.033X_6 + 0.093X_7 + 0.002BX_8$$

Here, the relationship between probability (diabetic) and $X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8$ is linear. Hence

$$Y = probability(diabetic) = \ell n\left[\frac{\theta_i}{1-\theta_i}\right]$$

$$= 28.106 + 0.054age + 14.866sex - 14.593MS + 0.019RF - 4.214HT + 0.033WT + 0.093BP + 0.002BSL$$

The (Y) above indicates that: (age, sex, risk factor, weight, blood pressure and blood sugar level) increases the probability of a patient being diabetic while marital status and height decreases the probability of a patient being diabetic.

More so, the "β" values are the logistics coefficients that can be used to create a predictive equation. In this research:

$$P(X / X = x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) = \frac{e^{(\beta_0+\beta_1x_1+\beta 2x_2+\beta_3x_3+\beta_4x_4+\beta_5x_5+\beta_6x\ +\beta_7x_7+\beta_8x_8)}}{1+e^{(\beta_0+\beta_1x_1+\beta 2x_2+\beta_3x_3+\beta_4x_4+\beta_5x_5+\beta_6x\ +\beta_7x_7+\beta_8x_8)}}$$

$$= \frac{1}{1+e^{(\beta_0+\beta_1x_1+\beta 2x_2+\beta_3x_3+\beta_4x_4+\beta_5x_5+\beta_6x\ +\beta_7x_7+\beta_8x_8)}}$$

Here, the relationship between the outcome and the predictors is non-linear.

$$P(diabetic) = \frac{e^{(28.106+0.054age+14.866sex-14.593MS+0.019RF-4.214HT+0.033WT+0.093BP+0.002BSL)}}{1+e^{(28.106+0.054age+14.866sex-14.593MS+0.019RF-4.214HT+0.033WT+0.093BP+0.002BSL)}}$$

$$P(diabetic) = \frac{1}{1+e^{(28.106+0.054age+14.866sex-14.593MS+0.019RF-4.214HT+0.033WT+0.093BP+0.002BSL)}}$$

Table 4.4: Model Summary

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*	*Hosmer and Lemeshow Test*		
			Chi-square	*Df*	*Sig.*
28.758[a]	0.321	0.781	1.088	8	0.998

Note: Estimation terminated at iteration number 8 because parameter estimates changed by less than. 001.

In Table 4.4, -2Log Likelihood (-2LL) is a measure of badness of- fit, illustrating error remaining in the model after accounting for all independent variables. The -2LL of 28.758 indicates that there is no significant error remaining in the model. The Nagelkerke R square shows that about 78 per cent of the variation in the outcome variable (probability of being diabetic) is explained by the model in table 1. A larger p-value of the Hosmer-Lemeshow test indicates a better match to claim that the model fits the data adequately.

Summary, Conclusion, Recommendations and Contribution(S) To Knowledge

Binomial regression model that incorporates individual characteristics and spatial distributed random effect was used to examine the chance of being Diabetic. It could be noted that, the covariates (age, risk factor, weight, blood pressure and blood sugar level) are statistically significant, because they all have a p-value of less than 0.05. Subsequently, the covariates (sex, marital status and height) are not statistically significant. The $Exp(\beta)$ representing odds ratio, which measures the extent to which the odds in favour of a positive response are raised when the level of the associated explanatory variable is raised from the reference level to the level specified in the table of results. This study measures the extent to which the odds in favour of being diabetic are raised when the levels of each explanatory variable is raised from the reference level (low) to the highest level (high). Thus, it shows that Risk Factor(RF) is the strongest determinant of being diabetic, having $Exp(\beta)$ of 70.981. Blood Sugar Level(BSL) is the second strongest determinant since the $Exp(\beta)$ accounts for 68.998. The third strongest determinant is Age since the $Exp(\beta)$ accounts for 65.055. Furthermore, Weight is the fourth strongest determinant having an $Exp(\beta)$ of 60.968. Blood Pressure(BP) accounts for $Exp(\beta)$ of 40.911. Height (HT) accounts for $Exp(\beta)$ of 12.015. Marital Status (MS) accounts for $Exp(\beta)$ of 10.000 and Sex accounts for $Exp(\beta)$ of 09.504. The explanatory variables (age, sex, risk factor, weight, blood pressure and blood sugar level) all have a positive influence on the response variable.

The -2Log Likelihood (-2LL) is a measure of badness of- fit, illustrating error remaining in the model after accounting for all independent variables. The -2LL of 28.758 indicates that there is no significant error remaining in the model. The Nagelkerke R square shows that about 78 per cent of the variation in the outcome variable (probability of being diabetic) is explained by the model in table 1. A larger p-value of the Hosmer-Lemeshow test indicates a better match to claim that the model fits the data adequately.

Conclusions

The study finds out the spread of diabetes in Taraba state Nigeria and also found out the probability of being diabetic and the highest population which is Jalingo becomes a factor while risk factor is the highest determinant of being diabetic.

Recommendations

On the basis of these research findings, the following recommendations were made;

i. More emphasis should be on risk factors, age people and Blood sugar level.
ii. Further study should be carried out on this research topic for constant monitor on the spread and reported cases of diabetes epidemic diseases in Taraba State Nigeria
iii. More emphasis should be lay on male diabetes patients because they are mostly the victims of the diseases compare to the female patients.
iv. The study results suggest that there are 'Diabetes hot-spots' in the study area. The government, and other Health related Non-Governmental Organizations should consider these results when planning Diabetes control measures.
v. Efficient data gathering systems should be employed to obtain data in most of the areas to improve prediction of the risks in the area.

Contribution(s) to Knowledge

This research study has been able to establish that the use of spatial binary logistic regression model to analyze the spread of Diabetes infection disease, explore the spatial and Demographic patterns and identify territories of high risk and model some important demographic and environmental variables that increase the risk of infection and also analyze the significant difference between the means of such variables in Taraba state using the data from the record department of the FMC Jalingo.

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